Fall risk assessment in the wild: A critical examination of wearable sensors use in free-living conditions

Mina Nouredanesh[1*†], Alan Godfrey[2†], Jennifer Howcroft[3], Edward D Lemaire[4,5] and James Tung[1]

[1] Department of Mechanical and Mechatronics Engineering, University of Waterloo, 200, University Ave. W, Waterloo, Canada

[2] Department of Computer & Information Science, Northumbria University, 2 Ellison Pl, Newcastle upon Tyne, UK.

[3] Department of Systems Design Engineering, University of Waterloo, 200 University Ave., Waterloo, Canada.

[4] Ottawa Hospital Research Institute, Centre for Rehabilitation, Research and Development, Ottawa, Canada.

[5] Faculty of Medicine, University of Ottawa, Ottawa, Canada.

† Equal contributor

*** Correspondence:**

Mina Nouredanesh

Department of Mechanical and Mechatronics Engineering,

University of Waterloo, 200,

University Ave. W,

Waterloo, Canada

Email: m2noured@uwaterloo.ca

Abstract

Background: Despite advances in laboratory-based supervised fall risk assessment methods (FRAs), falls still remain a major public health problem. This can be due to the alteration of behavior in laboratory due to the awareness of being observed (i.e., Hawthorne effect), the multifactorial complex etiology of falls, and our limited understanding of human behaviour in natural environments, or in the 'wild'. To address these imitations, a growing body of literature has focused on free-living wearable-sensor-based FRAs. The objective of this narrative literature review is to discuss papers investigating natural data collected by wearable sensors for a duration of at least 24 hours to identify fall-prone older adults.

Methods: Databases (Scopus, PubMed and Google Scholar) were systematically searched for studies based on a rigorous search strategy.

Results: The search yielded twenty-four studies, in which inertial sensors were the only wearable system employed for FRA in the wild. Gait was the most-investigated activity; but sitting, standing, lying, transitions and gait events, such as turns and missteps, were also explored. A multitude of free-living fall predictors (FLFPs), e.g., the quantity of daily steps, were extracted from activity bouts and events. FLFPs were further categorized into discrete domains (e.g., pace, complexity) defined by conceptual or data-driven models. Heterogeneity was found within the reviewed studies, which includes variance in: terminology (e.g., quantity vs macro), hyperparameters to define/estimate FLFPs, models and domains, and data processing approaches (e.g., the cut-off thresholds to define an ambulatory bout). These inconsistencies led to different results for similar FLFPs, limiting the ability to interpret and compare the evidence.

Conclusion: Free-living FRA is a promising avenue for fall prevention. Achieving a harmonized model is necessary to systematically address the inconsistencies in the field and identify FLFPs with the highest predictive values for falls to eventually address intervention programs and fall prevention.

Keywords: Falls in elderly; inertial measurement unit; wearable sensors; ambulatory fall risk assessment; free-living fall predictors

1.0 Introduction

It is estimated that 1 in 3 people globally over the age of 65 fall at least once each year [1], [2]. In addition to physical consequences (e.g., hip fracture, traumatic brain injury), falls can lead to negative mental health outcomes such as fear of falling and depression [3]. Falls among older adults tend to occur from multiple interacting factors [4], generally categorized as intrinsic/biological (e.g., a neurological mechanism or chronic condition such as Parkinson's disease, PD, muscle weakness), and extrinsic/environmental (e.g., slippery floor, obstacles, slopes, poor lighting) [5], [6], [7]. By identifying the various risks specific to an individual, fall risk assessment (FRA) can inform clinical decisions on the most appropriate preventive interventions to reduce the risk for fall events. To date, commonly used FRA methods involve easy-to-implement movement-based tasks with minimal equipment requirements, such as total time to complete a timed-up-and-go (TUG) [8], [9] or Tinetti Test [10]. Based on a meta-analysis, the diagnostic accuracy of TUG was poor to moderate for fall prediction in healthy high-functioning older adults and the cut-off thresholds for TUG-based identification of fallers were highly inconsistent within the included studies [11]. These limitations have led to a methodological shift towards the use of more detailed assessments. As the adopted gold standard, electronic-based tools, such as 3-dimensional motion capture and instrumented walkways, can be used to offer detailed quantitative assessments. Yet, these tools remain resource-intensive and fixed to specialized clinics/locations, offering snapshots during scripted functional tasks. Extrinsic risk factors for falls can be also recorded in (patient) self-reported diaries; however, this often lacks accuracy and adequate descriptions. To systematically investigate the impact of environmental conditions on older adults' tendency to fall, researchers have designed paradigms to mimic challenging natural conditions in a laboratory setting. For example, minimum foot clearance was measured in different lighting conditions in [12] to understand the nature of trips on stairs in older adults, where, in contrast to young adults, the lack of precautionary increase in older adults' foot clearance under reduced lighting contributed to falls on stairs. However, due to the observer effect during controlled gait and balance tests [13], supervised FRA measures may not necessarily reflect naturalistic and multitasking behaviour [14]–[16]. For instance, a weak association ($r = 0.333$, $p < 0.001$) between natural gait speed and in-laboratory gait speed was reported [17]. Similarly, free-living gait speed and step regularity measures were significantly lower compared with in-lab usual walking and tended to be more similar to in-lab dual-task walking [15]. Thus, novel free-living FRAs to identify fallers based on their free-living behaviour in their natural daily living environments could provide complementary information to supervised FRAs.

There have been a wide range of methods investigated to measure free-living mobility behaviour. Ambient sensors, such as radar [18], passive infrared [19], third-person video, and depth cameras [20]–[23] have been investigated as a means to extract gait parameters, detect falls, and track longitudinal changes in a person's mobility patterns. However, ambient sensors have limitations due to visual occlusions (e.g., furniture), inability to extract spatiotemporal data when full-body view is unavailable, and tracking the same person in spaces with multiple residents with similar body characteristics [24]. Moreover, they are restricted to the environments the sensors are installed in. In contrast, wearable sensors and their data have greater utility beyond the living space where ambient sensor data is recorded at the expense of additional burden in donning and maintaining devices. These technologies include wearables inertial sensors (e.g., accelerometers, gyroscopes, magnetometers), in-shoe plantar pressure sensors [25]–[27] and wearable cameras [28], [29].

Recent attention has focused on the identification of free-living fall predictors (FLFPs) from wearable-based data, such as total time walking/lying, frequency-based (e.g., the amplitude of dominant frequency) and temporal (e.g., step time) measures extracted from detected activity bouts (e.g., gait) and events (e.g., turns), towards profiling an individual's risk for falls. Several studies have shown that wearable-based FLFPs can either outperform or complement clinical (supervised) FRA tests [30]–[32]. For instance, a machine learning-based model developed on transition-based FLFPs outperformed its counterpart developed on clinical test scores (e.g., TUG) in discriminating between older fallers and non-fallers [30]. While this body of evidence has demonstrated promise, there is a high degree of inconsistency in the literature regarding the relationship between the extracted FLFPs and falls. Inconsistencies were also observed in data-driven and conceptual models proposed by the research groups to categorize FLFPs into domains (e.g., pace, asymmetry). At this time, due to the ongoing novel developments within the field, there are no clear solutions for transparent deployment of wearables for free-living FRA. Furthermore, the utility of existing free-living FRA methods to inform interventions remains limited, largely due to challenges interpreting unconventional metrics of free-living behaviour (e.g., entropy). After summarizing the key aspects of the experimental protocols used to collect free-living data (e.g., sensor placement, duration of free-living data collection, demographics), the current paper reviews sources of inconsistencies between the proposed free-living FRA approaches. At the end, recommendations were provided to inform future work towards achieving a harmonized free-living FRA model.

2.0 Search criteria

Three databases, Scopus, PubMed, and Google Scholar, were searched up to and including September 2019 (2010 to 2019). Search terms were [“home” or “unsupervised” or “real-world” or “community” or "ambulatory"] and [“fall” or “fall risk assessment”] and [“elderly” or “senior” or “aged”] and [“wearable sensor” or "accelerometers" or "inertial" or "wearable camera"]. Journal articles were included if they: 1) assessed the relationships between falls and features extracted from free-living data, and 2) collected data from wearables used by older adults (> 65 years) for a duration of at least 24 hours per participant. After the initial title screen, abstracts were reviewed. Twenty six (n=26) papers from databases met the inclusion criteria (Figure 1). Multiple papers from two research groups investigated the same/overlapping datasets or very similar sets of FLFPs: (a) Hausdorff and colleagues examined datasets from healthy older adults [32]–[35] and PD older adults [36], [37], and (b) Pijnappels and colleagues investigated: b-1. fall risk assessment in older adults (FARAO) dataset that was collected from >300 older adults [38]–[40], and b-2. overlapping (but different) subsets of FARAO dataset to address different research questions [16], [31], [41], [42]. Considering the high degree of overlap in b-2, the most relevant, largest sample, and/or highly cited paper examining fall risk was included for the purposes of this review [31] and [42] (see Figure 1). Therefore, the key methodological/demographic information from n=24 papers was extracted and provided in Tables 1-3 (the key aspects of [16] and [41] were highlighted in section 4).

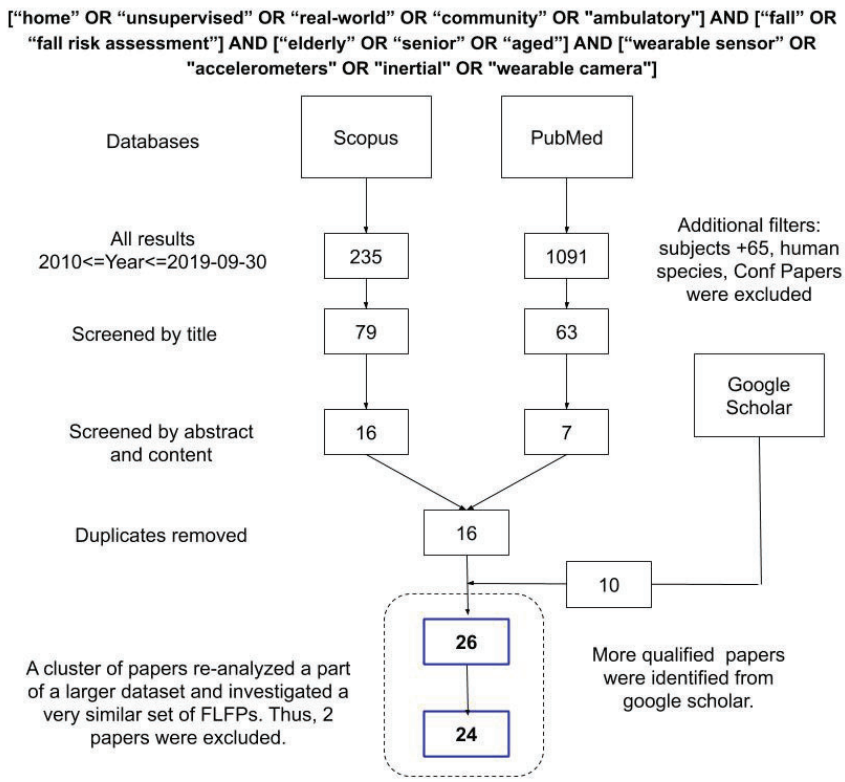

Figure 1: PRISMA flow chart of study design, illustrating search strategy results and filters at each stage of the study selection process.

3.0 Results

3.1 Study characteristics

Tables 1-3 show the study designs for capturing free-living data, demographic information, key methodological aspects, types of wearables, sensor anatomical location, general description of outcome measures, and the length of free-living recording for all included papers. The general procedure for wearable-based ambulatory FRA is shown in Figure 2.

In the reviewed studies, a range of inertial-based wearables were employed as described in Table 3. Most studies used a single tri-axial accelerometer-based wearable, with a minority using a uniaxial [43][44] or combined tri-axial accelerometer and tri-axial gyroscope (e.g., [30] [45]). Typically, one inertial-based wearable was worn on the lower back, including the pelvis, sacrum, and L3 to L5 vertebrae [30], [32], [42], [46], [47], [33]–[40], and midsagittal plane of the lower back [45]. Other wearable locations included chest/sternum [48]–[51], middle of the thigh [44], upper-thigh [43] dominant and nondominant hand/wrist [52]. In one study, multiple wearables were attached, two on shoes and one at L5 [53]. Free-living data were recorded from 24 hours [51] to 58 days (average over participants) in [48]. Most studies monitored community-dwelling older adults without neurological disorders (i.e., OA in Table 2). However, a number of studies also investigated differences between fallers and non-fallers in other populations: PD [36], [37], [43], [44], [46], dementia [51], [54], and varying frailty levels [50]. Additionally, fallers were further categorized as single fallers and recurrent fallers in two papers [43], [53].

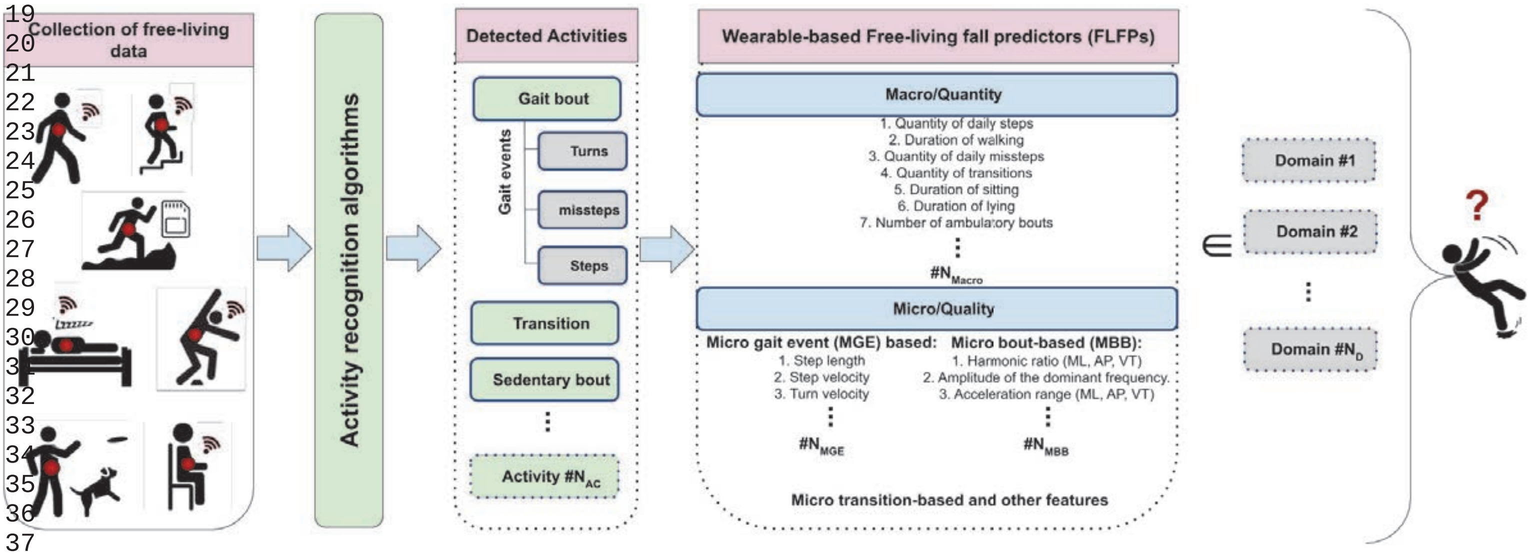

Figure 2: General process flow to acquire, process, and extract predictors for free-living fall risk assessment. Free-living data are collected using wearable sensors, segmented into bouts of activity types (e.g., gait, sitting), then predictors are extracted from activity bouts. There is a high degree of inconsistency in the literature in the categorization of extracted predictors into free-living FRA domains (dashed boxes).

Studies performed analysis to understand the relationships between wearable-based FLFPs and prospective falls [38], [39], [43], [50]–[52], [54], retrospective falls [30], [32]–[34], [36], [37], [44], [46], [47], [49], and both [42], [45], [53]. Falls were also categorized with respect to the associated pre-fall events and allocated to one of three categories: 1) transitions during changes of posture (e.g., turning, rising from chair); 2) ambulation (e.g., everyday walking activities, including stair climbing) and 3) advanced activities including complex high-risk motor tasks (e.g., skiing, hill walking) in one study [43]. Multivariate analysis or deep learning techniques were also applied to discriminate between fallers and non-fallers [39], [40], [54] without corresponding univariate analysis to investigate the individual FLFPs with respect to their predictive ability for falls.

<Table 1>

<Table 2>

<Table 3>

3.2 Free-living activity/event detection

Detecting bouts of activity were critical step in extracting FLFPs. The detection of ambulatory bouts were most common [30], [32], [44]–[51], [53], [33]–[35], [38]–[40], [42], [43] followed by, sitting [38], [42], [50], [51], lying [38], [42], [50], [51], sedentary (sitting and lying together) [44], [45], and standing [38], [42], [44], [50], [51]. Bout of activity detection was the initial methodological step required for the extraction of FLFPs from inertial sensor data (Figure 2). Transitions between consecutive ambulatory and sedentary bouts (i.e., walk-to-sit and sit-to-walk) were also quantified for insights to FRA [30], [38], [42], [50], [52].

Ambulatory bouts were further examined for detection of discrete gait events (Figure 2) such as initial and final contact within the gait cycle (e.g., in [32], [38], [42], [47], turns [45], [53], and missteps [37]. Missteps were broadly defined to include compensatory balance reactions (i.e., near-falls) to regain stability following a loss of balance.

3.2.1. Cut-off thresholds for identification of ambulatory bouts and turns

To identify an ambulatory bout, different minimum/maximum cut-off thresholds were defined according to steps, time or a combination of both [46], [48], [49] (Table 3). For example, Del Din et al. [46] referred to an ambulatory bout between 3 steps to 60s, 60-120s, and longer than 120s as 'short', 'medium', and 'long' walks, respectively. Alternatively, Brodie et al. considered short walks as those <7s and <8s and longer than three steps in two different studies [48], [49]. The minimum cut-off thresholds ranged from 1 step [43] to 120s [46] and a minimum of three steps was the most frequent cut-off threshold used within the reviewed studies from distinct datasets [46], [48]–[51]. Discrete angular thresholds were also used to identify turns. For instance, one study [53] examined those greater than 45^{o} but elsewhere different turn resolutions, e.g. small ($50-100^{o}$), medium ($100-150^{o}$), and large ($150-200^{o}$) were taken into account [45], Table 3. The detected activity bouts and events were later used independently for the extraction of FLFPs, which were statistically analyzed with respect to falls (Figure 2).

3.3. Conceptual models

As ambulatory bouts were the most investigated free-living activity for FRA, research groups defined different conceptual FRA models to classify and interpret a range of gait-based FLFPs. Each model consists of several domains, including a homogeneous group of FLFPs usually in terms of their mathematical description (Figure 3, models a [46], b [48], c [49], d [42], and e). Model e represents the merged domains from a set of research papers [32]–[34], [36] as discussed in section 2. In Figure 3-model e, complexity and local dynamic stability measures reported in [33], [34] were categorized into the same class because of their mathematical similarities (e.g., Lyapunov components [55]).

Broadly speaking, the reviewed literature examined the following features:

(1) the 'quantity' of gait events or ambulatory bouts and their duration over days/weeks [32], [36], [48], [49] also termed 'macro' (as discussed in 3.3.1) [43], [44], [46] and 'amount of gait' [38], [42],

(2) FLFPs that are obtained by performing a higher resolution analysis of the inertial signals or gait events, which include spatial (e.g. step length), temporal (step time), and frequency-based (e.g. harmonic ratio) features. These features termed as 'micro' (referring to more detailed micro-structural characteristics of gait as discussed in 3.3.2) [46] [44] [43] (Figure 3 model a) or 'quality' of gait (e.g. in [32], [36], [38], [42], [48], [49] (Figure 3),

(3) models of quantity/quality also extended to categorize turns [45], [53] and transition features [30], [52].

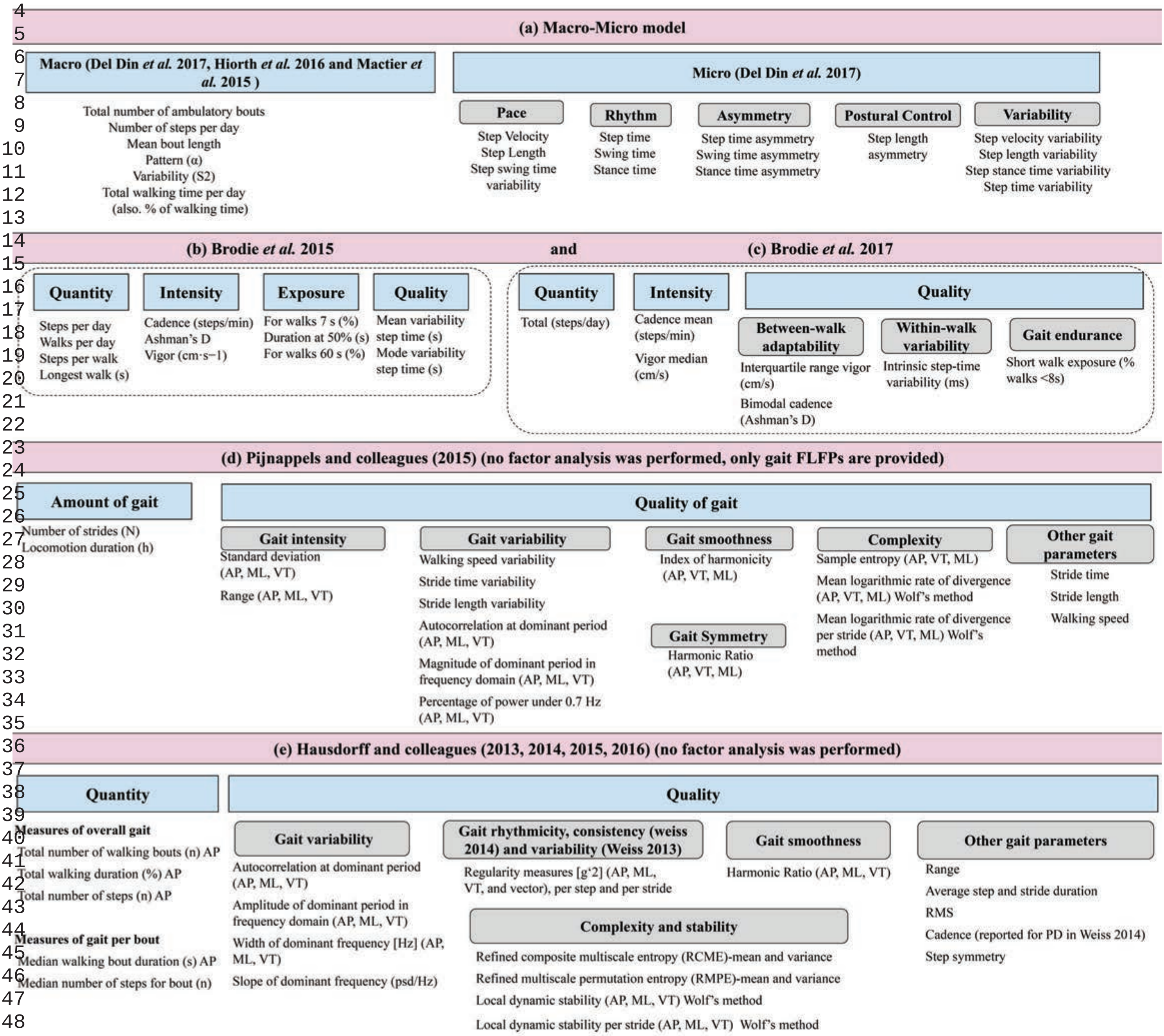

Figure 3: Conceptual models proposed by researchers to categorize gait-related features for fall risk assessment

As depicted in Figure 3-model d [42], gait quality was represented by six domains, each with its own set of FLFPs, such as: intensity (e.g., standard deviation, range); variability (e.g., autocorrelation, slope, magnitude); smoothness (e.g. index of harmonicity) and complexity (sample entropy). Alternatively, quality was presented within quantity-intensity-exposure-quality models (Figure 3, model b) and quantity-intensity-quality

(Figure 3-model c) comprising of different predictors within three domains (e.g., between-walk adaptability). Due to these inconsistencies associated with the use of 'quality', here the general categorization of FLFPs into macro and micro is used to describe quantity and quality of activities, respectively.

3.3.1 Macro/quantity FLFPs

Macro outcomes were generally described by duration or volume of an activity or the quantity of daily occurrences. Commonly used macro FLFPs include the number of ambulatory bouts [38], [42]–[44], [48], total steps within each bout [32], [36], [38], [42], [48], number of daily turns [45], [53], number of daily compensatory balance reactions [37], and number of transfers/transitions [30], [38], [42], [50], [52]. In addition to the aforementioned linear features, macro outcomes were utilized for non-linear analyses [43], [44], [46] (Figure 3-model a), including: 1. alpha (α), which is a unit-less FLFP derived from the power distribution of ambulatory bouts with respect to the cut-off thresholds and 2. within subject variability of bout length (S_2) obtained from a maximum likelihood technique as the distribution of bout length.

For sedentary (lying and sitting) and standing bouts, only macro features were investigated within studies [38], [42]–[45], [50], [51], which includes: total standing time [38], [42], [50], [51], total sedentary time [38], [42], [45], [50], [51], lying, sitting, and standing bout duration (mean, maximum, and 90th percentile) [50], [51], standing and sedentary bout duration variability [43], [44], number of sedentary and standing bouts [44], and alpha measures for sedentary and standing bouts [44].

3.3.2 Micro/quality FLFPs

Considering micro FLFPs that were investigated in studies, we categorized micro features into three main classes to aid consistency:

1. Micro gait event-based (MGE) FLFPs represent features requiring detection of gait events from ambulatory bouts in order to be quantified. For example, turn duration [45], [53] and step/stride length (e.g., examined in [38], [42], [46]) require detection of a gait event, such as turn and foot contacts, respectively. Consequently, established spatiotemporal gait parameters are generally considered as the MGE features,

including stance time, double support, step length. Turn-based MGEs were investigated in [45], [53], and they included mean turn velocity, peak turn velocity, turn duration, variability of turn duration, mean turn angle, turn angle variability and the logarithm of normalized jerk.

2. Micro ambulatory bout-based (MBB) outcomes include high-level temporal (e.g., root mean square) and frequency-based (e.g., mean logarithmic rate of divergence) FLFPs [32], [38], [42], [47] extracted from either the detected ambulatory bouts (based on the cut-off thresholds discussed in 3.2.1) or the subsequent epochs (discussed later), regardless of the enclosed gait events. MBB predictors were either direction-dependent features or based on signal vector magnitude. Directionally-dependent FLFPs were extracted from antero-posterior (AP), mediolateral (ML), vertical (VT) accelerations (e.g. regularity measures in [32], [36]). A number of FLFPs were extracted from the signal vector magnitude associated with the bout or epoch, including regularity measure [47], phase-dependent generalized multiscale entropy [40], and phase-dependent local dynamic stability [33]). To avoid possible sample size-related bias, each axial/signal vector segment attributed to a macro bout was split into fixed-size epochs for some studies. For example, bouts longer than 10sec and 60sec were split into the fixed 10 sec [47] and 50 s [34] epochs, respectively, and each epoch was used separately for the extraction of MBB outcomes.

   MBB features are less intuitive compared to spatiotemporal gait FLFPs; and are assumed to be indicative of different aspects of gait based on their mathematical description. For instance, slope, width, and amplitude of the dominant frequency in acceleration epochs were linked to variability of gait domain [32], [36], [38], [42], [47] and entropy measures (e.g., sample entropy [42], multiscale and phase-dependant entropy [34], [40]), were commonly extracted as potential markers of complexity domain (in [34] a lower entropy extracted from acceleration signals was linked to loss of complexity and an increased regularity).

3. Micro-transitions: similar to MBB predictors, these FLFPs consist of high-level temporal (e.g., peak velocity, range) or frequency-based (e.g. entropy) outcomes, which were either direction dependent (i.e., roll, pitch, yaw [30], [52]), or extracted

from the signal vector magnitude (e.g. jerk [52]) attributed to sit-to-walk (or stand) and walk (or stand)-to-sit transitions.

3.4 Data-driven models

One study presented a data-driven model by performing factor analysis to systematically categorize FLFPs into independent domains. In [38] principal component analysis (PCA) was performed on 75 outcomes including: *macro* (e.g., median number of strides in one ambulatory bout); MGE (e.g., stride time, stride length variability); MBB (e.g., mean logarithmic rate of divergence), and several questionnaire-based and test outcomes (e.g., inability to use public transportation, ability to ascend/descend stairs). Although PCA revealed 18 domains, wearable-based FLFPs were only loaded into 8 classes (considering their 3 highest weights that exceeded 0.3) as shown in Figure 4-model f.

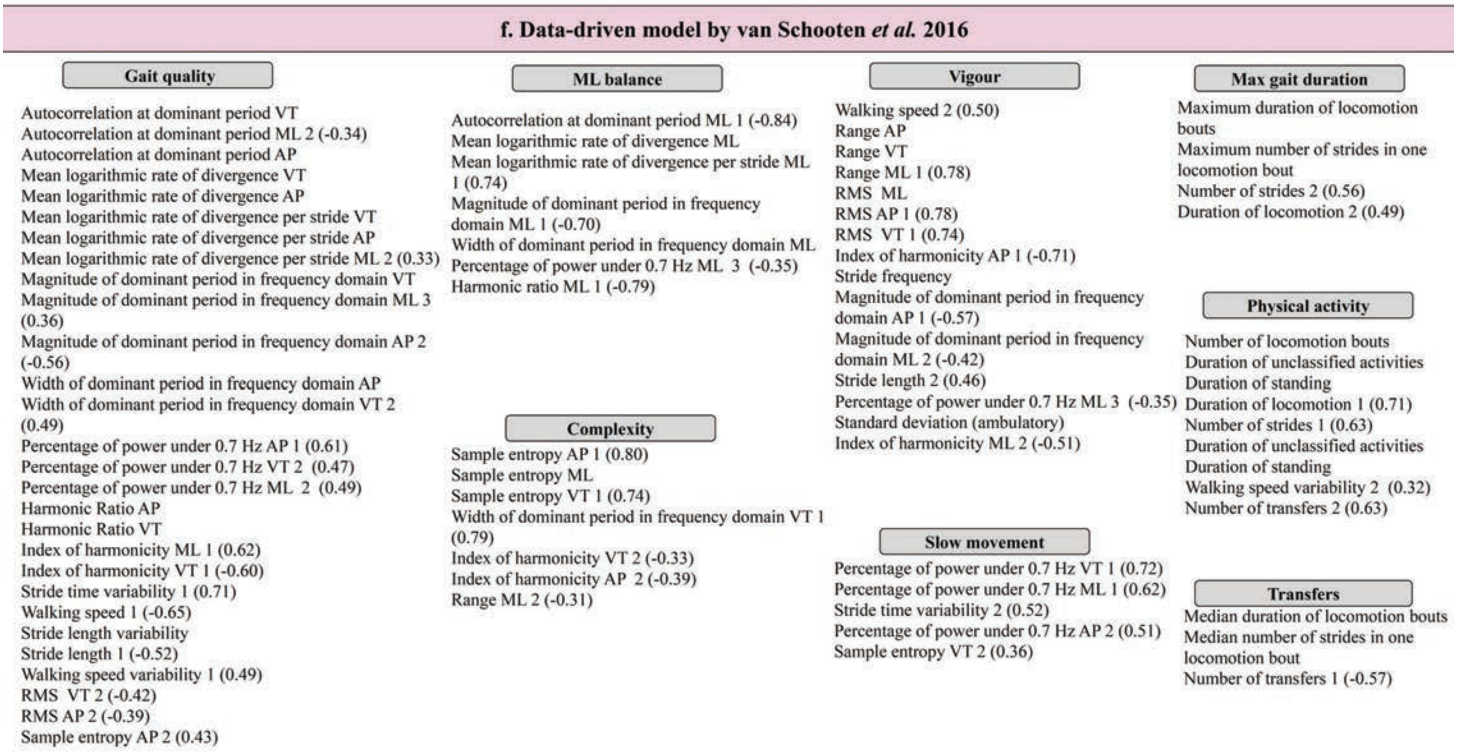

Figure 4: Data-driven model proposed by van Schooten et al, 2016 to categorize FLFPs. Only 8 relevant factors were taken into account (e.g., none of the FLFPs were loaded into domains such as history of falls, so those domains were not taken into account). If the FLFP is loaded into more than one domain (i.e., loading>0.3 in the paper), top three domains to which they indicate highest associations are indicated with integers (1 to 3). The numbers in parenthesis indicate the loading of the variable on varimax-rotated principal components.

4.0 Discussion

To date, inertial sensors using primarily acceleration signals, have been the preferred approach used to identify fallers based on their natural free-living behaviour over prolonged periods. These systems have demonstrated adequate capabilities to monitor and detect free-living activities, e.g., gait [30], [32], [44], [46]–[51], [33]–[35], [38]–[40], [42], [43], lying [38], [42], [50], [51] and gait events such as turns [45], [53]. However, it was observed that similar FLFPs that were examined by different studies indicated different levels of fall predictive ability; which can be due to the different experimental protocols used to collect free-living data (e.g. sensor placement, duration of free-living data collection, demographics), different mathematical/statistical methods, and algorithms used to define/detect activities (e.g., different cut-off thresholds). Due to these inconsistencies, developing conclusive interpretations of existing evidence remains limited. In the next subsections, the potential sources of inconsistency in methodology and categorization of FLFPs into domains are discussed. Following the sources of inconsistency, we provide recommendations towards harmonization of free-living FRA methods to advance the field.

4.1. Inconsistencies in free-living FRA models

4.1.1. Similar FLFPs, different predictive power for falls

a. Inconsistency in ambulatory bout and turn cut-off thresholds

Considering the initial step in processing free-living inertial-based signals is detecting bouts, the observed variability in defining ambulatory bout thresholds is a large source of inconsistency potentially affecting the fall predictive ability of the extracted bout-based FLFPs. For instance, walking duration and the number of ambulatory bouts (two FLFPs) obtained from bouts longer than 3s (i.e., 3s as the minimum cut-off threshold) showed no associations with falls [46]. However, by changing the minimum cut-off threshold to 120s, these same FLFPs (i.e., walking duration, # of bouts) showed a statistically significant predictive ability for falls [46]. Another example of inconsistent results arising from bout definition differences was variability in bout length. Using the definition of bouts >3s yielded significant association with falls; whereas variability in bouts >120 s was not significantly associated [46]. Similarly, while exposure to short duration walks <7s [48] and <8s [49]) was significantly associated with falls, exposure from walks shorter than 60 s was not discriminative ($p \cong 0.1$) [48].

It was also observed that discretizing angular cut-off thresholds can impact fall predictive power of turn-related FLFPs. For instance, although no relationship between the total number of daily turns (considering turns with different resolutions) and falls was reported [45], [53], after dividing them into three separate angular levels, the quantity of turns in each resolution turned out to be significantly lower for prospective fallers [45]. As only two studies were concerned with turns [45], [53]), the effects of varying cut-off threshold to determine bouts and/or events and subsequent impact on fall predictive ability remains underexamined.

b. Central tendency measures to estimate FLFPs

To extract FLFPs from free-living data, measures of central tendency used to calculate predictors were inconsistent between studies. The different statistical methods resulted in inter- and intra-study inconsistencies in terms of fall predictive values for similar FLFPs. For instance, mode of step time variability in [48] was significantly associated with falls; while the mean estimation did not indicate any relationship. In addition to medians, in [31] extremes of FLFPs were estimated (i.e., the 10th and 90th percentiles of gait characteristics) over 10s epochs/bouts; whereas in [38] only the medians of MBB FLFPs (e.g., entropy, amplitude of the dominant frequency) were reported. For instance, compared to median values, a stronger association was reported for some of the extreme estimations and falls [31]. Similarly, macro gait features such as ambulatory bout duration, mean [46], [50], [51], maximum [32], [38], [42], [48], [51], 90th percentiles [50], and medians [32], [36], [38], [42], [48] were reported. Overall, the lack of consistency limits the capacity to compare across studies and synthesize the evidence.

c. Free-living data collection protocols

Across the reviewed studies, inconsistent data collection protocols may play a key role in fall predictive ability of FLFPs. Specifically, length of data collection, sampling frequency, and wearable location were inconsistent across studies. Although eight days of free-living data was reported to be sufficient for the identification of fall-prone individuals [48], only one day of free-living data per participant was investigated in [50], [51]. In [41] up to five days was reported to be required for the estimation of median duration of locomotion bouts; while a minimum of two days of free-living data resulted an inter class correlation greater than 0.7 for most activities (sitting, standing and shuffling, except for lying). Sampling frequency was inconsistently used within the studies, ranging from 10 Hz in [43] to 100 Hz in [52] (see Table 3). Considering the impact of sampling frequency on the wearable unit battery life [56], the identification of the optimal sampling frequency requires further investigation. Moreover, estimates of gait characteristics may suffer from errors due to discrepancies in accelerometer location [57]. Although lab-based data suggest that inertial-based wearables mounted on shins can outperform other anatomical locations [58] for detection of fallers, no study has considered this location for the collection of free-living data with lower back as the most frequently used location for sensor placement. To date there is no consensus about the most robust location for free-living FRA, which requires further exploration.

4.1.2 Inconsistencies in the proposed free-living FRA models

Efforts to develop an FRA model based on predictors generated from wearables is needed to interpret FLFPs related to fall risk. These interpretations are critical to understanding the underlying causes or factors indicating risks and informing interventions for clinicians. In contrast, black-box models (e.g., deep models) that estimate risk without interpretive value are less useful. The reviewed studies with models demonstrated considerable inconsistency, likely reflective of the on-going advancement in the field.

As discussed in 3.3, we found quality as the most inconsistently used term with discrepancies in definition and application. There were many inconsistent terminologies observed across a range of domains and FLFPs within the examined models. For instance, harmonic ratio was an indicator of gait smoothness in conceptual model e and but an indicator of symmetry in model d (instead, index of harmonicity was the measure of smoothness in model d). In some cases, different terminologies were used to describe the same FLFP. For example, endurance and exposure were defined by the same calculation in [48], [49], albeit described in different domains in models b and c, respectively (Figure 3). In another case, the term 'vigour' was used to describe a domain (Figure 4) [38] and defined as a FLFP (root mean square of vertical angular velocity) in models b and c [48], [49].

In contrast to conceptual models (e.g., Figure 3, models d and e), where all of the AP, ML, VT, and vector-based components of the same MBB FLFP where considered under the same domain (e.g., harmonic ratio in ML, AP, and VT were considered under gait smoothness), different anatomical directions of some of the MBB FLFPs were loaded onto independent domains in data-driven model f (Figure 4). Many of the FLFPs extracted from ML acceleration were loaded into a distinct domain called 'ML balance' (e.g., harmonic ratio in ML direction was loaded into ML balance, while the other two components were considered under quality). Similarly, index of harmonicity in AP direction was loaded into vigour; although the other two directions were loaded into quality. It is clear the proposed models are a work in progress as the field is continually advancing. The existing inconsistencies highlighted in the current review suggest the need for deeper discussion to harmonize interpretive models.

4.2. Recommendations for harmonization and clinical implications

4.2.1. Precise activity recognition algorithms

One possible reason for inconsistencies in fall predictive power of FLFPs is the use of black-box thresholds in activity recognition algorithms [59], [60] in some of the studies, resulting in a low specificity and clarity to analyze free-living activities. For instance, studies included here were only concerned with general types of activities, such as ambulation, standing, sitting, and lying. A subset of studies differentiated between patterns of gait, such as ascending/descending stairs, or fast walking. For instance, [31] excluded locomotion bouts suspected to contain running episodes as they caused severe outliers in FLFP estimations for some of the participants. Additionally, turns and compensatory balance reactions were not excluded from ambulatory bouts before the extraction of MBB features. For instance, the misstep detection method in [37] revealed a number of suspected missteps from 5-second ambulatory bouts. However, in a subsequent study [36], MBB features were extracted from the same dataset without excluding those suspected missteps, which may have affected the fall predictive values of the MBB features.

Multimodal approaches, such as a combination of IMUs, surface electromyography [61], electroencephalogram [62], heart rate variability and ECG [63] and pressure-sensitive shoe-insoles [25]–[27] may increase the specificity of activity recognition algorithms, and therefore, to improve the sensitivity of FLFPs to identify fallers. As an example, using a force sensing insole equipped with an IMU and a barometric sensor, a framework to discriminate between level walking and stairs patterns of gait was developed and evaluated [64]. State-of-the-art algorithms, such as long-short term memory and deep convolutional neural networks have achieved near-human accuracy levels in detection of a broad range of activities from multimodal public datasets [65], which can be employed as a replacement to threshold-based methods to detect a broader range of natural activities. Only one study [39] investigated the use of deep learning models to identify fallers based on their preprocessed 10-second walking patterns; where deep models slightly outperformed the baseline approach based on the biomechanical FLFPs as discussed in [38].

4.2.2. Interpreting FLFPs by acquiring contextual information

In [66] it was shown that the mobility measures are affected by the environmental features (e.g., sidewalk slopes and crossings) and it was hypothesized that subjects would adapt to challenging environments by decreasing gait speed, increasing cadence, and shortening stride length. Moreover, a higher variability in ML direction, e.g., a lower amplitude of the dominant frequency, could indicate a higher adaptability to the environment [32]. However, the intrinsic meaning of these measures and terminologies (e.g., adaptability) in different anatomical directions and contexts remains unclear, inertial sensors do not provide sufficient information on human-environment interaction. Although applying cutting-edge algorithms (as discussed in 4.2.1) can boost the interpretation of context (e.g. stair climbing, walking downhill), the validity of these algorithms in complicated free-living scenarios needs to be carefully examined (also refer to the last column in Table 3, which shows the algorithms used in included studies were not mostly validated in free-living conditions).

In [67] time-stamped self-reporting (voice recordings) was along with IMU data to increase the interpretability of IMU data and to locate compensatory balance reactions (slips, trips, stumbles) collected in 4 weeks. However, such a tool may also suffer from subjectivity and under-reporting. On the other hand, egocentric first-person video, acquired via body-worn cameras have been used as a gold standard [59] for the purpose of validating IMU-based algorithms or identification of specific events or environmental features [68] [14],

[69]. First person video captures more contextually relevant information on the properties of the environment compared to IMU alone. This includes, but is not limited to, varying slope and surface navigation as well as static and dynamic objects (e.g. obstacles, pedestrians) that influence mobility behaviour. As an alternative to frame-by-frame investigation (visual inspection) of first person video data, algorithms are in development to automatically detect extrinsic risk factors from first person video data. For instance, machine learning (e.g., convolutional neural networks) and image processing (e.g., Gabor Barcodes) techniques have shown promising performance in automatic detection of environmental fall-related hazards, including slope changes (e.g., stairs, curbs, ramps) and different surfaces (e.g., gravel, grass, concrete) [70], [71]. By augmenting IMU approaches with egocentric videos, more insight can be readily gained from specific motoric activity. For example, gait data pertaining to micro/quality gait (from an IMU) within a new residential environment under low-level lighting conditions (video) or within crowded open spaces during daylight offer different challenges for fallers. Combined IMU and video approaches may allow healthcare professionals to target individualised approaches for rehabilitation strategies, ensuring safer navigation and reduced falls.

4.2.3. An all-inclusive data-driven model

As discussed in 4.1.1, different hyperparameters, such as ambulatory bout length, central tendency measures, and data collection protocols, such as the length of free-living data and sampling frequency, can impact fall predictive power of FLFPs. However, there is not sufficient evidence indicating the optimal values for these hyperparameters to achieve the highest predictive values specific to each FLFP. Moreover, many features, such as those quantifying different aspects of compensatory balance reactions, micro-transition- (e.g. jerk, entropy) and foot clearance-based measures were not investigated in any of the previous data-driven models (e.g., Figure 4-model f and controlled models such as [72]). Therefore, debate continues about their real identity in terms of their allocation to free-living domains. The aforementioned gaps in the literature indicate a need to obtain a standardized model to define discrete independent domains by performing factor analysis on a comprehensive range of wearable-based FLFPs derived from a broad range of video-validated activity bouts. This comprehensive set may also include similar FLFPs but different in terms of hyperparameters (e.g., ambulatory bout lengths, turn cut-off thresholds, and central tendency measures). It is also feasible to simulate shorter/longer collection periods, and sampling rates (by up- and down-sampling signals) and examine FLFPs' sensitivity with respect to these factors. Performing factor analysis on the aforementioned comprehensive set of features altered based on different hyperparameters would permit deeper insights on developing more structured free-living models and provides more information on the differences between laboratory and free-living features in prediction of falls. While a deeper discussion on developing better models by including established lab-based models of fall risk is beyond the scope of the current paper, efforts towards a more comprehensive fall risk model leveraging both laboratory and free-living sources of evidence are on-going. Such efforts will better inform pragmatic efforts for which gait and other functional movements may be useful to identify surrogate markers of incipient pathology, inform diagnostic algorithms, track disease progression, and measure the efficacy of interventions [73].

5.0 Conclusion

Overall, free-living FRA using wearables is a promising avenue for fall prevention; however, due to the high level of heterogeneity in the use of wearables; e.g., sensor location, diverse cohorts, stratified employment (e.g., 1 vs 7 days), definition of free-living domains, and the selection of free-living bout resolutions, the evidence for the relationships between FLFPs and falls has remained inconclusive. Moreover, many FLFPs were specific to research groups and were not systematically investigated in an all-inclusive factor analysis. Therefore, achieving a data-driven model is necessary to systematically identify the FLFPs, bout resolutions, and domains with the highest predictive values for falls to eventually address intervention programs and prevent older adults from falling. Publishing well-annotated video-validated free-living datasets to support harmonization efforts is strongly recommended.

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Conflict of interest

The authors declare that they have no conflict of interest.

Table 1: Study designs for capturing free-living data. Dashed lines separate the relevant studies published from the same research group or from overlapping datasets. ACC: accelerometer, Gyro: gyroscope, 3D: three-dimensional, FLFP: free-living fall predictor.

Study	Free-living data-log duration	Type of activities	Modality(ies)	Sensor placement
Weiss (2013) [32]; Ihlen (2015, 2016a, 2016b) [33, 34, 35]	3 days	Gait	DynaPort MoveMonitor	At the L5 level
Iluz (2014) [37]	3 days	Missteps	DynaPort Hybrid (ACC+Gyro)	Lower back(L4-5)
Weiss (2014) [36]	3 days	Gait		
Iluz (2015) [30]	3 days	Sit-to-walk and walk-to-sit transitions	One ACC+Gyro	Lower back
Rispens (2015a) [47]	2 weeks	Amount of physical (in-)activity and quality of daily-life gait	DynaPort MoveMonitor	Around the waist and set along the lumbar spine
van Schooten (2015a) [42]	8 days	Amount of physical (in-)activity	DynaPort MoveMonitor	Dorsally on the trunk at L5
Rispens (2015b) [31]	1 week	Amount of physical (in-)activity and quality of daily-life gait		
van Schooten (2016) [38] Nait Aicha (2018) [39] and Ihlen (2018) [40]	1 week	Bouts of locomotion, sitting, lying, standing only gait in Nait Aicha (2018) [39] and Ihlen (2018) [40]	DynaPort MoveMonitor	At the L5 level
Brodie (2015) [48]	Mean 58 days/participant: Fallers: 44.0(29.0) days, NFs: 67.0(29.0) days	Activities during walking hours were monitored, only gait was investigated	Philips (Senior Mobility Monitor) pendant (ACC+Barometer)	Sternum Level
Brodie (2017) [49]	7 days (≥6hr data per day)	Activities during walking hours were monitored, only gait was investigated	Philips (Senior Mobility Monitor) pendant (ACC+Barometer)	Sternum Level
Mancini (2016) [53]	≈10 hours/day for 7 days	Turning mobility	3 IMUs(APDM Opal)	One on belt (L5), 2 on shoes
Leach (2018) [45]	5-9 days	Turns and gait	Android smartphone (3DACC+3DGyro) and uFALL app	Midsagittal plane of the lower back
Mohler (2016) [50]	48 hours	Walking, sitting, standing, lying and postural transitions (all time except while showering)	PAMSys BioSensic	Into a T-shirt with a device pocket at sternum level
Pozaic (2016) [52]	7 days	Sit-to-stand transitions (focus of the study)	Bosch sensor tech Gmbh (sD ACC, 3D gyro, 3D magnetometer)	One attached to Wrist
Mactier (2015) [43]	7 days	Gait	activPAL (uniaxial ACC)	Upper thigh
Hiorth (2016) [44]	7days (at least 4 days)	1) Volume, 2) pattern, 3) accumulation, 4) variability of sedentary behavior (sitting, lying), standing, and ambulatory bouts	activPAL	Middle of thigh
Del Din (2017) [46]	7 days	Macro- and micro-gait parameters (spatiotemporal)	Axivity AX3	Lower back
Schwenk (2014) [51]	24hours	Walking,sitting,standing,lying	Physilog (2ACC+1Gyro)	Attached to the chest (pocket)
Gietzelt (2014) [54]	7 days after each visit (4 visits in 8 months)		One SHIMMER sensor	

Table 2: Demographic data, Fs: fallers, NFs: non-fallers, OA: community-dwelling older adults, PD: people with Parkinson's disease, f: female, m: male, FLFP: free-living fall predictor. Dashed lines separate the relevant studies published from the same research group or from overlapping datasets.

Study	Specific disease (Yes/No)	Participants' Number, Age, female:male		Categorization of fallers and non-fallers based on: Prospective falls	Retrospective falls
Weiss (2013) [32]; Ihlen (2015, 2016a, 2016b) [33, 34, 35]	No	NFs: 39, 78.77(4.39)y, fs: 64.10%	Fs:32, 77.86(5.09)y, fs: 65.62%	12 subjects reported ≥ 2 falls 6 months following the experiment [1]	≥ 2 falls one year prior to measurements
Weiss (2014) [36]	All PD	NFs: 67(40 to 85y)	Fs: 40(40 to 85y)	1 year follow-up(each month returned) [2], 14 NFs turned to Fs	$\geq$1 fall prior year
Iluz (2014) [37]	All PD	NFs+Fs:40, 62.16(10.02)y, Fs:9, f:m=8:32		N/A	≥ 2 falls in the past 6 months
Iluz (2015) [30]	No	NFs: 38, 78.65(4.35), f: 63.15%	Fs: 33, 77.89(4.99), f: 66.66%	No	$\geq$2 falls in the previous year
Rispens (2015a) [47]	No	110 (Fs+NFs),78.4(7.8)y, f:m= 77:33		No	$\geq$2 falls in the previous year; 1.2(1.6) falls in 12 months prior the measurements
van Schooten (2015a) [42]	No	Retrospective-NFs: 109, Prospective-NFs: 110 NFs+Fs: 169, 75.4(6.8)y, f: 52.1%	Retrospective-Fs: 60, Prospective-Fs: 59	≥ 1 Falls in 6 months follow-up	Falls in the preceding 6 months
Rispens (2015b) [31]	No	NFs: 132, 75.1(6.6)y, f: 50%	Fs: 70, 75.6(6.1)y, f: 53%	≥ 1 falls 6 months follow-up	Used in models but FLFPs were analyzed with respect to P falls
van Schooten (2016)[3] [38]	No	Complete data for 294/319 participants were analyzed. Total 294 participants: 75.3(6.8)y, f: 50.8%, 48.8% had ≥ 1 falls in past year, 25.2% had ≥ 2 falls in past year		Initially 6 months, extended to 12 months if willing to continue)	≥ 1 and ≥ 2 falls in past year
Nait Aicha (2018) [39]		101/296 participants had ≥ 1 fall (34.1%), m: 74.1%			
Ihlen (2018) [40]		Total NFs: 199; Matched NFs for Single-Fs: 75.9(6.7)y, f: 51%; Matched NFs for Recurrent-Fs: 75.2(6.4)y, f: 48.8%	Single-Fs: 58, 76.1(6.8)y, f: 51%; Recurrent-Fs (2< falls): 46, 75.5(6.7)y, f: 48.8%	6 months follow-up	
Brodie (2015) [48]	No	NFs: 11, 84.0(7.9)y, f:m=7:0	Fs: 7, 82.2(5.9)y, f:m=7:4	No	$\geq$1 falls in the past 12 months
Brodie (2017) [49]	No	NFs: 63, 75.8(7.3)y, sex: 0.48(0.50) (considering f=1 and m=0)	Fs: 33, 74.9(8.5)y, sex: 0.81(0.39) (considering f=1 and m=0)	No	≥ 1 fall in prior 12 months

[1]Statistical analysis was done with respect to retrospective falls only

[2]Statistical analysis for single FLFPs was only done with respect to retrospective falls; but separate survival analysis/Cox regression was perfomed for prospective falls

[3]Fall risk assessment in older adults (FARAO) dataset

Mancini (2016) [53]	No	NFs: 16, 83.9(7.0)y, f:m=3:13	Recurrent-Fs: 7, 88.4(8.8)y, f:m=2:5‖ Single-Fs=12, f:m=8:4, 86.0(7.0)y	6 months following the 7 day recording, 7/35 experienced one or more fall	N≥2 falls in the previous year
Leach (2018) [45]	No	Retrospective-NFs: 154 Prospective-NFs = 153	Retrospective-Fs = 6 Prospective-Fs = 7	≥ 2 falls in 12 months	≥ 2 falls in 12 months
Mohler (2016) [50]	Non-frail, pre-frail and frail	Non-frail NFs: 23, 74.7 (6.7)y, fs: 19 Pre-frail NFs: 38, 79.7(8.5)y, fs:28 Frail NFs: 10, 86.6(5.9)y, fs:7	Non-frail Fs: 20, 74.4(6.6)y, fs: 17 Pre-frail Fs: 19, 79.4(8.8)y, fs:15 Frail Fs: 9, 80.9(9.8)y, fs:9	Falls in the 6 months after the initial baseline study visit	N/A
Pozaic (2016) [52]	No	NFs: 123, 72.4(5.6)y, fs in NFs:57.7%	Fs: 13, 74.2(5.3)y, fs in Fs:69.2%	≥ 1 fall in one month follow-up (overall 21 falls, 4 participants ≥2 falls)	N/A
Mactier (2015) [43]	All PD (no healthy control)	111 PD, NFs: 70(52), Single-Fs: 17(12), Recurrent-Fs: 24(19), categorized based on pre-fall event: 14 transition-Fs, 17 ambulation-Fs, 7 advanced-activity-Fs		12 months	N/A
Hiorth et al. (2016) [44]	All PD	NFs: 28	Fs: 20	N/A	6 months fall history
Del Din (2017) [46]	OA and PD	OA-NFs: 50, PD-NFs:15; For all NFs: 69.05(7.67)y f: 56%	OA-Fs: 122, PD-Fs:155; For all Fs: 73.33(6.78)y, f: 42%	N/A	≥2falls past 6 months, NFs: not fallen in at least 18 months
Schwenk (2014) [51]	People with dementia	NFs: 49, 81.8(5.9)y, m: 34.7%	Fs: 28, 82.0(7.1)y, m: 21.4%	3-months follow-up	
Gietzelt (2014) [54]	People with dementia	At the beginning 40 Fs+NFs (fs: 20), 76.0(8.3)y, Fs=13 (n=8 fell once, n=2 fell 2 times, n=1 fell 4 times, n=2 fell 5 times)		A prospective cohort study with 3 phases: short-term (start to month 2): n=38(2 drop-outs (DOs) , 6 falls, 18 missed, (month 2-4): n=33 (5 DOs), 11 falls, 2 missed, (month4-6): 30 (3 DOs): 8 falls, 5 missed, (month 6-8):n=28 (2 DOs), 1 fall, 11 missed.	

Table 3: Bout of walking and activity definitions. ACC: accelerometer, Gyro: gyroscope, 3D: three-dimensional. Dashed lines separate the relevant studies published from the same research group or from overlapping datasets. FLFP: free-living fall predictor, OA: older adults, VT: vertical, AP: anterior-posterior, F: faller, NF: non-faller.

Study	Bout of activities/walking definition and Specific constraints	signal identifying bout	Sampling rate	Validation
Weiss (2013) [32]; Weiss (2014) [36], Ihlen(2015, 2016a,2016b) [33, 34, 35]	Ambulatory bouts$\geq$ 60s were taken into account for FLFP extraction (dissected to 60-second intervals, e.g., in [32]). The bouts were identified based on two filters: 1. a signal magnitude area (SMA) threshold-based activity detection monitor, 2. a threshold of the energy in the frequency domain (windows with energy ¡0.05 were excluded). In Ihlen (2016) [34] ambulatory bouts $\geq$60s were divided into 50-second epochs for the extraction of entropy/complexity features.	ACC(3D)	100Hz	In Weiss (2013) [32] it was mentioned that the validated methods discussed in papers by Weiss (2011), Moe-Nolssen (2004) and Yack (1993) were used to quantify different aspects of gait. Validation in free-living conditions: N/A.
Iluz (2014) [37]	5-second windows (running window of 5s) with 2-15 steps were detected and considered for FLFP extraction	ACC(3D), Gyro(3D)	100Hz	To develop the algorithm 29 missteps (negotiating obstacles while walking) were captured in a laboratory setting and more than 60 hours of data were recorded. Their rule-based algorithm achieved a 93.1% hit ratio and 98.6% specificity on this dataset.
Iluz (2015) [30]	Detection of the subject's gross activity (e.g., gait, sitting) was performed based on the local mean of the acceleration signals (e.g., negative values for local mean of the vertical acceleration signal indicate lying; while positive values may correspond to: gait, standing, or sitting), with additional criteria applied to increase the robustness of the detection. The transitions were identified after detection of sitting and gait episodes	ACC (3D), Gyro (3D)	100 Hz	Validation in free-living conditions: N/A.
Rispens (2015a) [47]	Locomotion episodes $\geq$ 10s, each episode was split into 10-second epochs (to avoid sample-size related bias)	ACC(3D)	100Hz	Validation in free-living conditions: N/A.
van Schooten (2015a) [42] and van Schooten (2016) [38] and Rispens (2015b) [31], Nait Aicha (2018) [39]	Locomotion episodes $\geq$ 10s, each episode was split into 10-second epochs (to avoid sample-size related bias), sufficient quantity of gait bouts ($\geq$ 50s) per participants to be included in analysis (18 participants were excluded, 4 excluded in vas Schooten (2015), Participants with $\geq$ 75%wear time. In Rispens(2015b) [31] locomotion bouts with suspected running events were discarded.	ACC(3D)	100Hz	Bouts of non-wearing, locomotion, sitting, lying and standing were identified using manufacturer's algorithm (Dijkstra et al.) Validation in free-living conditions: N/A.
Ihlen (2018) [40]	First, ambulatory bouts$\geq$3s were identified by a commercially available activity detection algorithm. Then, 3D ACC signals attributed to ambulatory bouts$\geq$30s were included for the analysis. The included ambulatory bouts were split into equal-sized 30-second epochs to provide a consistent sample size to estimate entropy measures. The epochs were further checked (visually) and non-walking activity bouts were excluded. Inclusion criteria for walking epochs were: (a) distinct impact peaks in VT and/or AP component of the ACC signal, (b) distinct cyclical ACC pattern in VT and/or AP component(s), and (c) criteria (a) and (b) were satisfied for at least 80% of the epochs, where max 20% was considered for gait initiation, turning or transitional micro-breaks.			The aforementioned inclusion criteria were based on the visual inspection of fast, normal and slow walking pattern discussed in a 'validation' study for activity detection in OA by Bourke et al., (2017).
Brodie (2015) [48]	Ambulatory bouts were defined by consecutive heel strikes identified by vertical acceleration peaks in the level 4 and 5 Daubechies 5th-order wavelet decomposition. Daily-life gait quantity was quantified by: (a) Steps per day from ambulatory bouts>=3 steps), (b) Walks per day (of ambulatory bout>=8 steps), (c) Steps per walk (mean of walks>=8 steps). For intensity and quality analyses: ambulatory bout>=7 steps and for exposure analysis ambulatory bout <7s and <60s were taken into account.	ACC(3D)	50Hz (25Hz barometer-not used)	Validation in free-living conditions: N/A.
Brodie (2017) [49]	Walks were defined by 3 consecutive heel strike peaks less than 3s apart. Short walk exposure was calculated by the percentage of walking duration <8s.	ACC(3D)	50Hz (25Hz barometer-not used)	Validation in free-living conditions: N/A.

Mancini (2016) [53]	10s≤ambulatory bouts longer or equal to 10s were first detected using 3D angular velocity signals and then were further investigated for the detection of turns, 0.5s<turn-Duration<10s 45deg ≤turn angles. Turn angles were obtained by integrating the angular rate of the lumbar sensor about the V axis.	3D angular velocity signals	128 Hz	In El-Gohary (2013), compared to Motion Analysis and video, the algorithm maintained a sensitivity of 0.90 and 0.76 and a specificity of 0.75 and 0.65, respectively. The turn detection algorithm was further applied to data collected in the home from 12 PD and 18 control subjects and the algorithm successfully detects turn characteristics.
Leach (2018) [45]	Turn type and angular range of turn include 50-100deg, 100-150deg and 150-200deg (analyzed only if happened during gait with 0.5-5s duration). The turn detection algorithm was based on the angular rotational rate of the pelvis about the vertical axis.	ACC(3D) + Gyro(3D)	N/A	The turn detection algorithm was validated in El-Gohary (2013) as above.
Mohler (2016) [50]	Walking bouts >5s and > 3 steps were taken into account (based on Tosizadeh(2015))	ACC(3D)	N/A	Validation in free-living conditions: N/A.
Pozaic (2016) [52]	N/A	ACC(3D)	100Hz	Particular trigger events (such as rotation of the wrist above a predefined threshold), as well as periodical or motionless/dormancy situations after these events. An ACC-based arm swing detector was used for the detection of the walking phase. Methods was validated in a pilot study with 28 OA (65-90y), who performed eight different types of the sit-to-stand transitions in a controlled environment (i.e. camera-supervised lab) as part of the protocol that simulated activities of daily living. The algorithm showed 71.4% precision for the non-dominant hand and 67.9% precision for the dominant hand.
Mactier (2015) [43]	Windows of 15s were used and walking episodes of ≥one step were taken into account for FLFP extraction.	ACC(1D)	10Hz	Previous work in OA against other accelerometer and video recordings in people with rheumatoid arthritis during simulation of ADL in the laboratory. It was mentioned that the validated activePAL can identify postures (e.g. sitting, lying, standing).
Hiorth (2016) [44]	Ambularory bouts<10 strides, 10-50 strides and >50 strides were taken into account.	ACC(1D)	20Hz	Validation in free-living conditions: N/A.
Del Din (2017) [46]	All ambulatory bouts >3 steps (minimum bout length) were taken into account for the analysis. For for micro-gait FLFPs, ambulatory bout> 10s were taken into account. For macro-gait FLFPs, ambulatory bouts> 3steps (short), Ambulatory bout> 60s (medium) and Ambulatory bout>120s (large) were considered. A threshold of 2.5s was set for the maximum resting period between consecutive ambulatory bouts	ACC(3D)	100Hz	The ambulatory bout detection algorithm was validated in a study with wearable cameras (Hickey et al., 2017). Characteristics of gait were selected based upon a model of gait validated both in OA and in people with PD in two distinct studies.
Gietzelt (2014) [54]	Ambulatory bouts of ≥ 20 s were taken into account.	ACC(3D)	N/A	Validation in free-living conditions: N/A.
Schwenk (2014) [51]	A walking period was defined as an interval with at least 3 successive steps as described in the validation study of the Physilog. Activities with < 3 steps were considered as standing (e.g. working in the kitchen and moving < 3 steps).	Two ACCs and one Gyro	N/A	It was mentioned that the algorithm was sensitive (87-99%) and specific (87-99.7%) for detection of the physical activity pattern in different samples of OA and patients. Validation in free-living conditions: N/A.

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Conflict of interest

The authors:

Mina Nouredanesh (m2noured@uwaterloo.ca), Alan Godfrey (alan.godfrey@northumbria.ac.uk), Jennifer Howcroft (jenny.howcroft@uwaterloo.ca), Edward D Lemaire (elemaire@ohri.ca), and James Tung (james.tung@uwaterloo.ca)

declare that they have no conflict of interest.